

# Measurements, uncertainties and probabilistic inference/forecasting

Giulio D'Agostini

Università di Roma La Sapienza e INFN  
Roma, Italy

<https://www.roma1.infn.it/~dagos/AQ2021/>  
(temporary web page)

# Falsificationism and p-values

- ▶ `arXiv:physics/0412148 [physics.data-an]`
- ▶ `arXiv:1112.3620 [physics.data-an]`
- ▶ `arXiv:1609.01668 [physics.data-an]`

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Let's review the practice and what is behind it ⇒

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It seems OK – '*obvious*'! – but it is indeed naïve for several aspects.

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is this extension legitimate?

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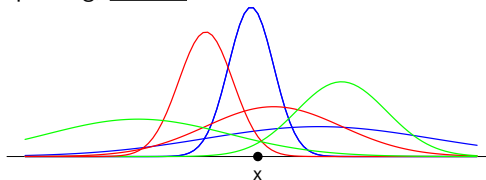
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⇒ Having observed any value  $x$ , none of  $H_i$  can be, strictly speaking, falsified.



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⇒ logically speaking, Popper's falsificationism has to be considered ... falsified!



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*[ I am particularly worried about claims concerning our health, or the status of the Planet, etc. ... ]*

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**But** it is behind the rational behind  
the statistical hypothesis tests!

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In particular

- ▶ A cause might produce a given effect with very low probability, and nevertheless could be the most probable cause of that effect, **often the only one!**



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(From the logical point of view the situation gets worsened:

→ **conclusions depend on events not actually observed!**)

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→ the test variable (' $\theta$ ') is absolutely arbitrary:

$$\theta = \theta(x)$$

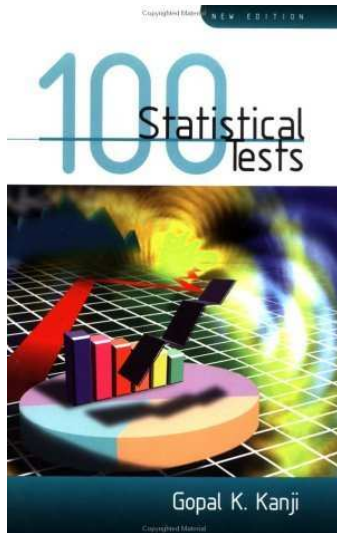
$$\rightarrow f(\theta) \text{ [p.d.f]}$$

$$\text{Experiment: } \rightarrow \theta_{obs} = \theta(x_{obs})$$

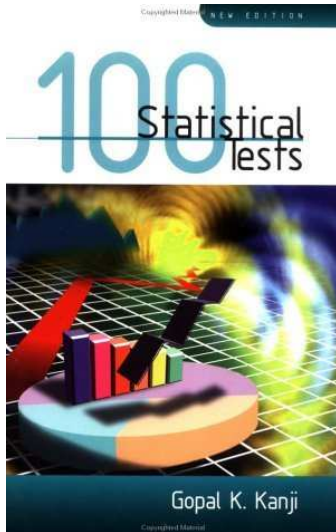
$$\text{p-value} = P(\theta \geq \theta_{obs}) \quad (\text{'one tail'})$$



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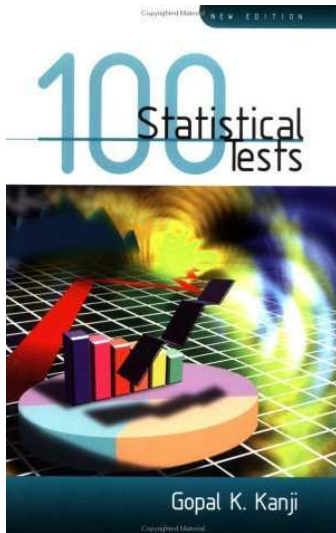


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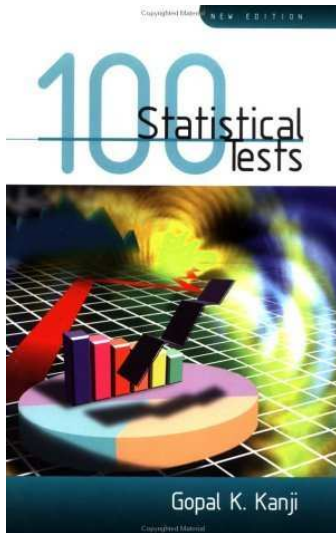
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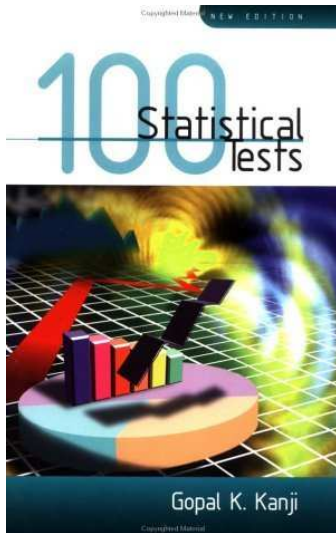
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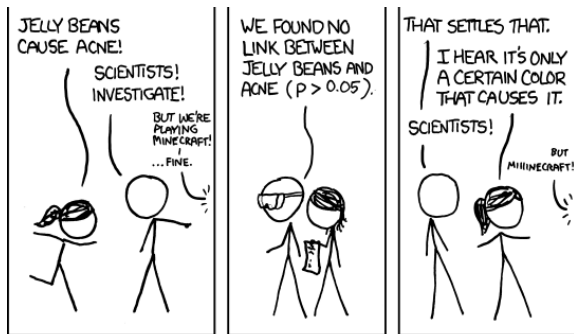
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⇒ practitioners chose the one that provide the result they like better:  
→ *like if you go around until "someone agrees with you"*
- ▶ personal **'golden rule'**:  
*"the more exotic is the name of the test, the less I believe the result"*, because I'm pretty sure that several 'normal' tests have been discarded in the meanwhile...

## Or look around, searching for 'significance'

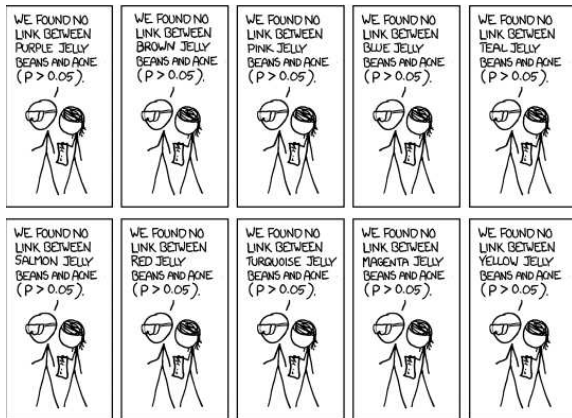
If changing the test does not help, change hypotheses...



[<http://xkcd.com/882/>]

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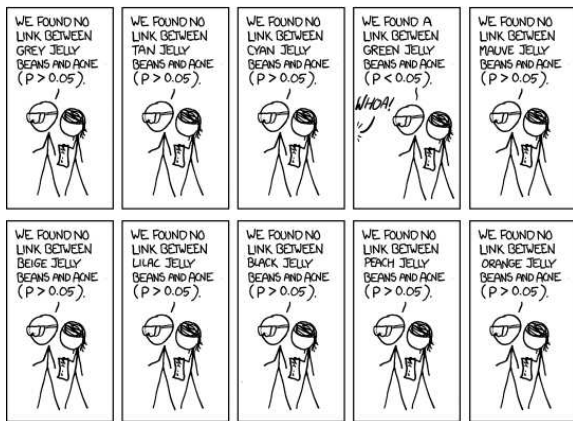
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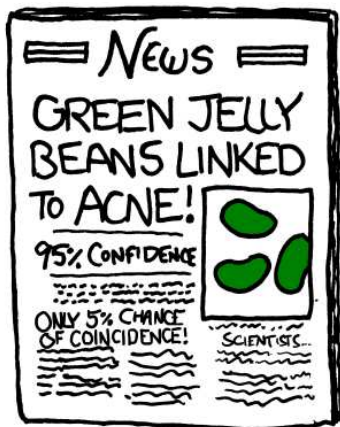


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# P-hacking (“p-value hacking”)

The ‘science’ of inventing significant results. . .

## p-hacking, or cheating on a p-value

June 11, 2015

By arthur charpentier

Share

(This article was first published on [Freakonometrics](#) » [R-english](#), and kindly contributed to [R-bloggers](#))

Yesterday evening, I discovered some interesting slides on False-Positives, p-Hacking, Statistical Power, and Evidential Value, via [@UCBITSS](#)’s post on Twitter. More precisely, there was this slide on how cheating (because that’s basically what it is) to get a ‘good’ model (by targeting the  $p$ -value)

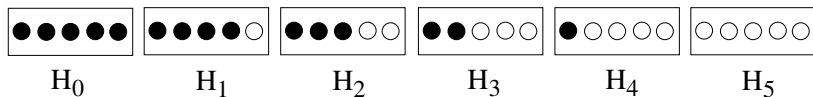
1. Stop collecting data once  $p < .05$
2. Analyze many measures, but report only those with  $p < .05$ .
3. Collect and analyze many conditions, but only report those with  $p < .05$ .
4. Use covariates to get  $p < .05$ .
5. Exclude participants to get  $p < .05$ .
6. Transform the data to get  $p < .05$ .

<http://www.r-bloggers.com/p-hacking-or-cheating-on-a-p-value/>

► Google for “p-hacking”

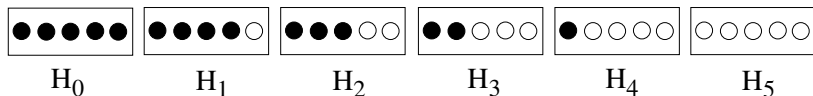
# Continuing from last lecture

## Which box? Which ball?



Let us take randomly one of the boxes.

## Which box? Which ball?



Let us take randomly one of the boxes.

We are in a state of uncertainty concerning several *events*, the most important of which correspond to the following questions:

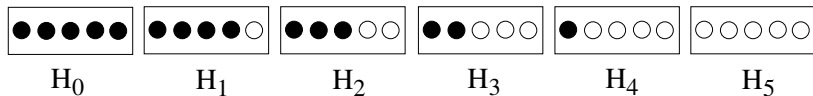
- (a) Which box have we chosen,  $H_0, H_1, \dots, H_5$ ?
- (b) If we extract randomly a ball from the chosen box, will we observe a white ( $E_W \equiv E_1$ ) or black ( $E_B \equiv E_2$ ) ball?

Our certainties:

$$\bigcup_{j=0}^5 H_j = \Omega$$

$$\bigcup_{i=1}^2 E_i = \Omega.$$

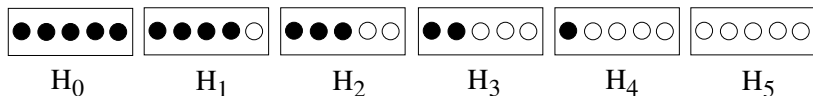
## Which box? Which ball?



Let us take randomly one of the boxes.

- ▶ What happens after we have extracted one ball and looked its color?
  - ▶ Intuitively feel *how to roughly change* our opinion about
    - ▶ the possible cause
    - ▶ a future observation

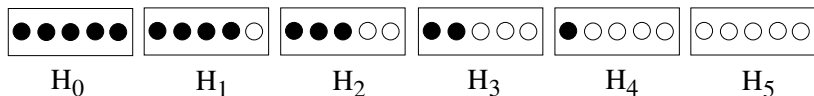
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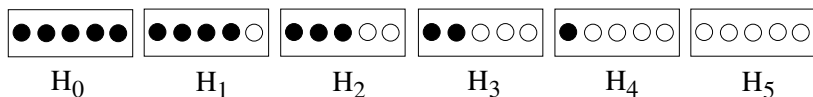


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**Note:** In general, we are uncertain about all the combinations of  $E_i$  and  $H_j$ :

$$E_1 \cap H_0, E_1 \cap H_1, \dots, E_2 \cap H_5,$$

and these 12 **constituents** are not equiprobable.

## Subjective nature of probability

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Probability depends on **the status of information of the *subject*** who evaluates it.

## Probability is always conditional probability

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$$P(E) \longrightarrow P(E | I_s(t))$$

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Examples:

- ▶ tossing coins and dice;
- ▶ the three box problem.

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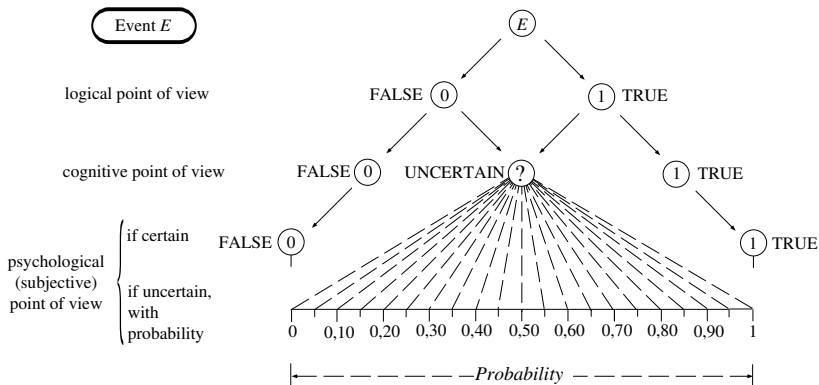
⇒ How much we believe something

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→ ‘Degree of belief’ ←

# False, True and probable





# Beliefs and 'coherent' bets

Remarks:

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Is a 'conventional' **95% C.L.** lower/upper bound a **19 to 1 bet?**

## Standard textbook definitions

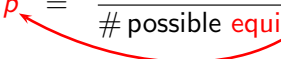
$$p = \frac{\# \text{ favorable cases}}{\# \text{ possible equiprobable cases}}$$

$$p = \frac{\# \text{ times the event has occurred}}{\# \text{ independent trials under same conditions}}$$



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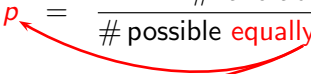
It is easy to check that 'scientific' definitions suffer of circularity

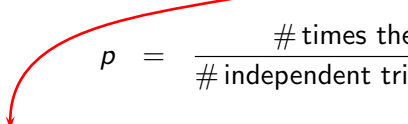
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$$p = \frac{\# \text{ favorable cases}}{\# \text{ possible equally possible cases}}$$


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Note!: *“lorsque rien ne porte à croire que l'un de ces cas doit arriver plutôt que les autres” (Laplace)*

Replacing 'equi-probable' by 'equi-possible' is just cheating students (as I did in my first lecture on the subject. . .).

## Standard textbook definitions

It is easy to check that 'scientific' definitions suffer of circularity, plus other problems

$$p = \frac{\# \text{ favorable cases}}{\# \text{ possible } \text{equiprobable} \text{ cases}}$$

$$p = \lim_{n \rightarrow \infty} \frac{\# \text{ times the event has occurred}}{\# \text{ independent trials under same condition}}$$

Future  $\Leftrightarrow$  Past (belief!)

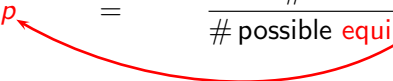
$n \rightarrow \infty$ :  $\rightarrow$  "usque tandem?"


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Future  $\Leftrightarrow$  Past (belief!)

Future  $\Leftrightarrow$  Past: avoid the end of the *inductivist turkey!*

## 'Definitions' → evaluation rules

Very useful **evaluation rules**

$$A) \quad p = \frac{\# \text{ favorable cases}}{\# \text{ possible equiprobable cases}}$$

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If the **implicit beliefs** are **well suited** for each case of application.

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**BUT** they cannot define the concept of probability!

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In the probabilistic approach we are following

- ▶ Rule *A* is recovered immediately (under the assumption of equiprobability, when it applies).
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⇒ **Laplace's rule of succession** (see later)



# Mathematics of beliefs

The good news:

*The basic laws of degrees of belief are the same we get from the inventory of favorable and possible cases, or from events occurred in the past.*

It can be proved that

*the requirement of **coherence** leads to the famous 4 basic rules  $\implies$*

[ Details skipped. . . ]

## Basic rules of probability

1.  $0 \leq P(A | I) \leq 1$
2.  $P(\Omega | I) = 1$
3.  $P(A \cup B | I) = P(A | I) + P(B | I)$  [if  $P(A \cap B | I) = 0$ ]
4.  $P(A \cap B | I) = P(A | B, I) \cdot P(B | I) = P(B | A, I) \cdot P(A | I)$

Remember that probability is always conditional probability!

$I$  is the background condition (related to information ' $I'_S$ ')  
*(Note: In the original image, the  $I'_S$  is written in red)*

→ usually implicit (we only care about 're-conditioning')

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**Note:** 4. does not define conditional probability.  
(Probability is always conditional probability!)

# Mathematics of beliefs

An even better news:

The fourth basic rule  
can be fully exploited!

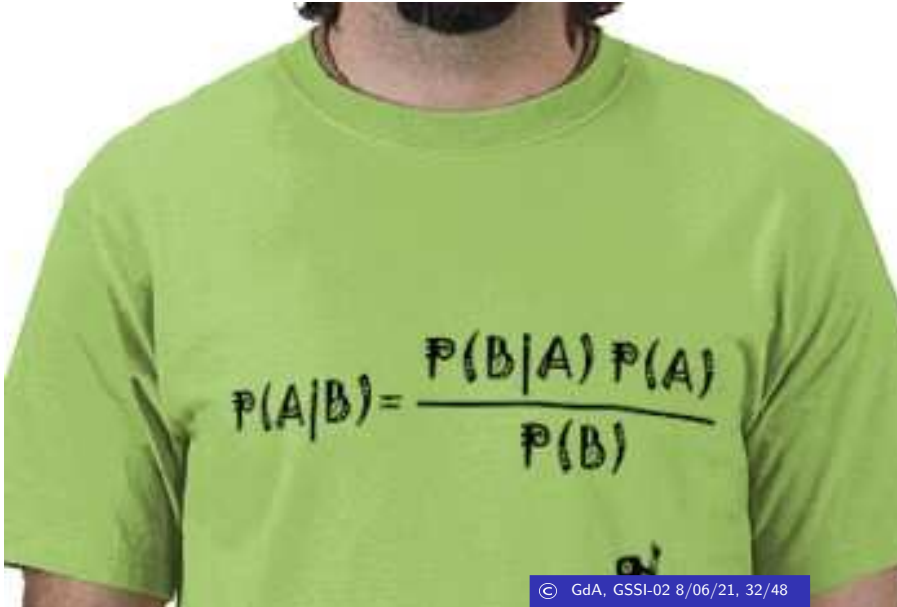
# Mathematics of beliefs

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(Liberated by a **curious ideology** that forbids its use)

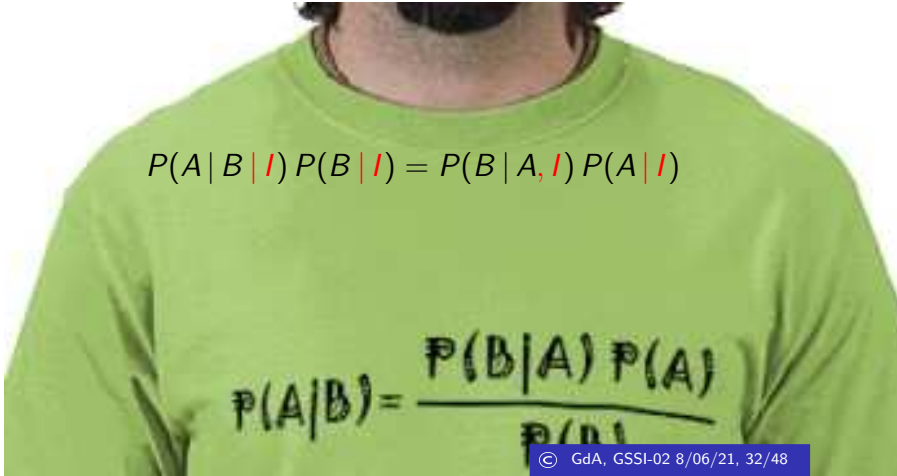
A simple, powerful formula

A person is wearing a bright green t-shirt. Printed on the front of the t-shirt in black ink is the formula for conditional probability: 
$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

The formula is written in a hand-drawn style. The numerator consists of  $P(B|A)$  followed by  $P(A)$ , with a horizontal line underneath. The denominator is  $P(B)$ .

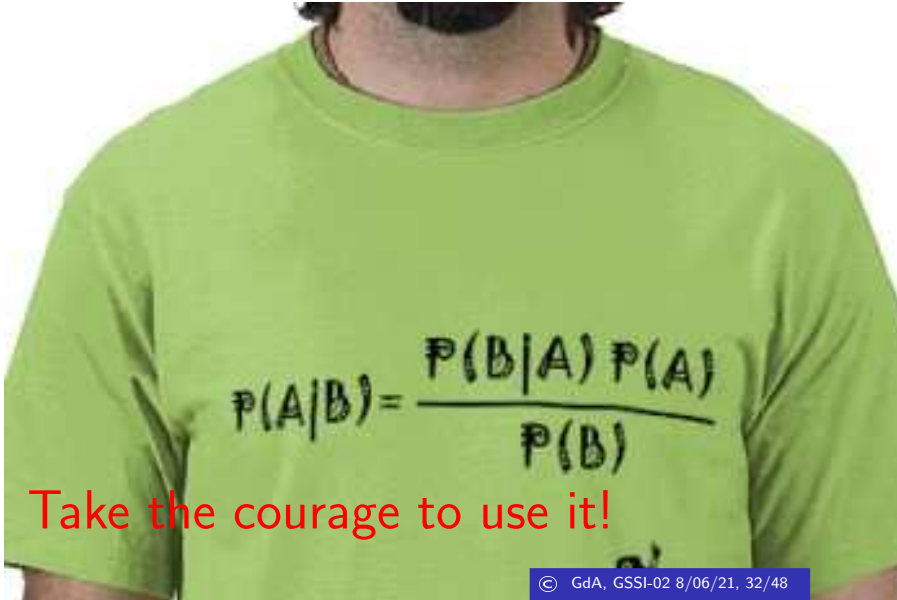
## A simple, powerful formula

$$P(A | B, I) P(B | I) = P(B | A, I) P(A | I)$$

A person wearing a green t-shirt with a handwritten formula on it. The formula is Bayes' theorem: 
$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

The person is wearing a green t-shirt with the formula  $P(A|B) = \frac{P(B|A) P(A)}{P(B)}$  written on it in black marker.

A simple, powerful formula

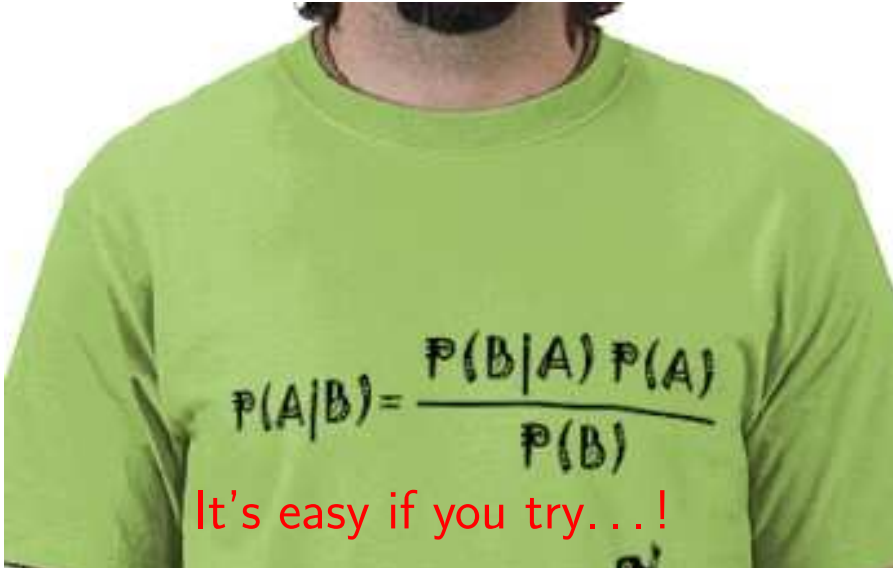
A person is shown from the chest up, wearing a bright green t-shirt. The t-shirt has a mathematical formula printed on it in black ink. The formula is Bayes' theorem: 
$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

The person's face is partially visible at the top of the frame, showing a beard and dark hair. The background is plain white.

Take the courage to use it!




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The person's face is partially visible at the top, showing a beard and mustache. The background is plain white.

It's easy if you try...!

A simple, powerful formula



A person wearing a green t-shirt with the Bayes Theorem formula written on it. The formula is  $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$ .

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

[ Bayes Theorem ]

## A nice and powerful formula!



GdA and Allen Caldwell, Stellenbosch, South Africa, November 2013

[T-shirts kindly provided by Pangea Formazione]

# Laplace's "Bayes Theorem"

"The greater the probability of an observed event given any one of a number of causes to which that event may be attributed, the greater the likelihood of that cause {given that event}.

$$P(C_i | E) \propto P(E | C_i)$$

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"The greater the probability of an observed event given any one of a number of causes to which that event may be attributed, the greater the likelihood of that cause {given that event}. The probability of the existence of any one of these causes {given the event} is thus a fraction whose numerator is the probability of the event given the cause, and whose denominator is the sum of similar probabilities, summed over all causes.

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$$P(C_i | E) = \frac{P(E | C_i) P(C_i)}{P(E)}$$

*(Philosophical Essai on Probabilities)*

[In general  $P(E) = \sum_j P(E | C_j) P(C_j)$  (weighted average, with weights being the probabilities of the conditions) if  $C_j$  form a complete class of hypotheses]

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“This is the **fundamental principle** (\*) of that branch of the analysis of chance that consists of reasoning a posteriori **from events to causes**”

(\*) In his “Philosophical essay” Laplace calls ‘principles’ the ‘fundamental rules’.



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Most convenient way to remember Bayes theorem

# Laplace's teaching

$$\frac{P(H_0 | \text{data})}{P(H_1 | \text{data})} = \frac{P(\text{data} | H_0)}{P(\text{data} | H_1)} \times \frac{P(H_0)}{P(H_1)}$$

- ▶ We should possibly use the data, rather than the test variables ' $\theta$ ' ( $\chi^2$  etc);  
[although in some case 'sufficient summaries' do exist]

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 $\Rightarrow$  **falsification** (the 'serious' one) is a **corollary of the theorem**, rather than a principle.
- ▶ There is **no conceptual problem** with the fact that  $P(\text{data} | H_1) \rightarrow 0$  (e.g.  $10^{-37}$ ), provided the ratio  $P(\text{data} | H_0)/P(\text{data} | H_1)$  is not undefined.

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If  $H_0$  and  $H_1$  are 'complementary', that is  $H_1 = \overline{H_0}$ , then

$$\text{posterior odds} = \text{Bayes factor} \times \text{prior odds}$$

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(Left as exercise)

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- ▶ dependence on **priors**;
- ▶ dependence on the fact that the **test performances unavoidably some degree of uncertainty**.

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- ▶ **Certainly!** I agree!

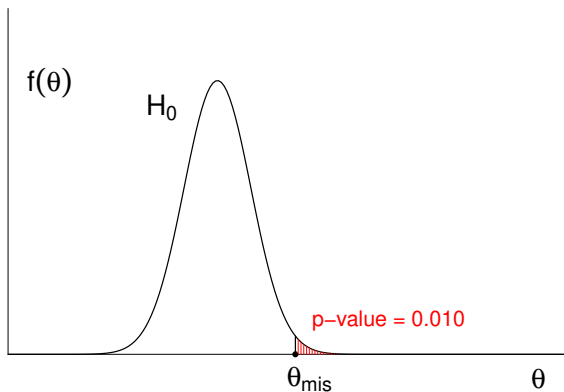
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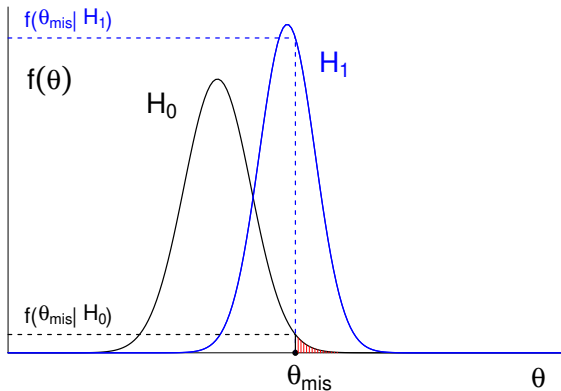
- ▶ **Certainly!** I agree!  
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- ▶ But now we are also able to **explain the reason**.

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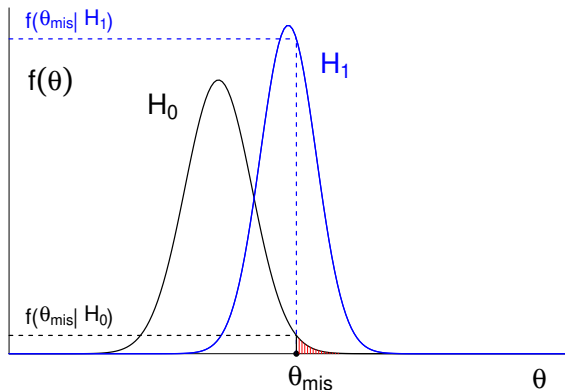
Why should the observation of  $\theta_{\text{mis}}$  should diminish our confidence on  $H_0$ ?

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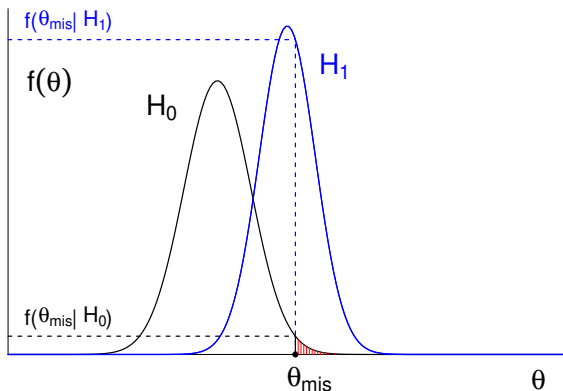
Because *often* we give *some chance* to a possible alternative hypothesis  $H_1$ , even if we are not able to exactly formulate it.

## But statistical tests do work!



Indeed, what really matters is not the **area** to the right of  $\theta_{\text{mis}}$ .  
What matters is the ratio of  $f(\theta_{\text{mis}} | H_1)$  to  $f(\theta_{\text{mis}} | H_0)$ !  
 $\Rightarrow$  to a 'small' area it corresponds a 'small'  $f(\theta_{\text{mis}} | H_0)$ .

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But is the alternative hypothesis  $H_1$  is unconceivable, or hardly believable, the 'smallness' of the area is irrelevant



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Arguments used to derive Gaussian distribution

- ▶  $f(\mu | \{x\}) \propto f(\{x\} | \mu) \cdot f_0(\mu)$
- ▶  $f_0(\mu)$  'flat' (all values a priori equally possible)
- ▶ posterior maximized at  $\mu = \bar{x}$

# The Gauss' Bayes Factor

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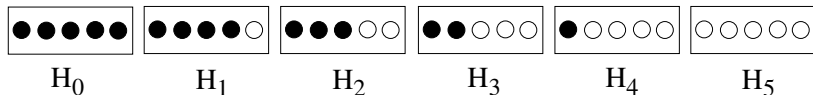
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(And, by the way, Enrico Fermi derived analysis tools based on *his* Bayes Theorem...

⇒ arXiv:physics/0509080 [physics.hist-ph] )

## Application to the six box problem



Remind:

- ▶  $E_1 = \text{White}$
- ▶  $E_2 = \text{Black}$

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Our **prior** belief about  $H_j$

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Probability of  $E_i$  under a well defined hypothesis  $H_j$   
It corresponds to the 'response of the apparatus' in measurements.

→ **likelihood** (traditional, rather confusing name!)



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'decomposition law':  $P(E_i | I) = \sum_j P(E_i | H_j, I) \cdot P(H_j | I)$   
(→ Easy to check that it gives  $P(E_i | I) = 1/2$  in our case).

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## Let's play!

- ▶ Hugin Expert (Lite – demo version);
- ▶ R scripts

# Playing with the six boxes

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**NO!**

- ▶ Don't even think: frequentists refuse to assign probabilities to hypotheses (in general), to causes, to true values, etc.  
(And you have seen the results...)

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- ▶ Update probabilities of next extraction: *prediction*:

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**No real distinction between inference and prediction**



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- ▶ Write down the **joint distribution** of all variables in the game:

$$P(C, B, \underline{E}, \underline{R})$$

$$\underline{E}: E_i^{(1)}, E_i^{(2)}, E_i^{(3)}, \dots$$

$$\underline{R}: R_i^{(1)}, R_i^{(2)}, R_i^{(3)}, \dots$$

- ▶ **Condition** on the 'observations':

$$P(C, B, \underline{E}, \underline{R}^{(k>n)} | \underline{R}^{(k\leq n)}) = \frac{P(C, B, \underline{E}, \underline{R})}{P(\underline{R}^{(k\leq n)})}$$

**No real distinction between inference and prediction**

(We shall see it later in the case of *continuous distributions*)

The End